View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by Southern Methodist University

SMU Data Science Review

Volume 5 | Number 1

Article 9

2021

Enhanced Data Science Methods for Freight Optimization at Kelly-Moore Paints

Lance Dacy
Southern Methodist University, ldacy@smu.edu

Reannan McDaniel
Southern Methodist University, rmcdaniel@mail.smu.edu

Shawn Jung
Southern Methodist University, shawnj@mail.smu.edu

Follow this and additional works at: https://scholar.smu.edu/datasciencereview

Part of the Business Administration, Management, and Operations Commons, Business Analytics Commons, Business Intelligence Commons, and the Operations and Supply Chain Management Commons

Recommended Citation

Dacy, Lance; McDaniel, Reannan; and Jung, Shawn (2021) "Enhanced Data Science Methods for Freight Optimization at Kelly-Moore Paints," *SMU Data Science Review*: Vol. 5 : No. 1 , Article 9.
Available at: https://scholar.smu.edu/datasciencereview/vol5/iss1/9

This Article is brought to you for free and open access by SMU Scholar. It has been accepted for inclusion in SMU Data Science Review by an authorized administrator of SMU Scholar. For more information, please visit http://digitalrepository.smu.edu.

Enhanced Data Science Methods for Freight Optimization at Kelly-Moore Paints

Lance Dacy, Reannan McDaniel, Shawn Jung

Master of Science in Data Science
Southern Methodist University, Dallas TX 75275 USA
ldacy@smu.edu, rmcdaniel@mail.smu.edu, shawnj@mail.smu.edu

Abstract. Kelly-Moore Paints is a paint manufacturing company founded in San Carlos, California in 1946 by William Kelly and William Moore. It has stores located in California, Texas, Oklahoma, and Nevada. They currently own 11 42' trailers, contract 4 distinct drivers, and service 44 stores Monday-Thursday from its Texas Distribution and Manufacturing Center in Hurst, TX. Given that transportation costs are typically the highest in the supply chain costs, this study will employ data science techniques to ensure the transportation routing, store ordering mechanism, and trailer utilization are at the best efficiency possible given the current ordering patters of the stores. Using an approach based on the Ant Colony Algorithm (ACO) [7] and Traveling Salesman Problem [8], the team will optimize a model of convergence that seeks to allow Kelly-Moore to fine-tune their operation to recover transportation costs that could be leaking from inefficient use of trailer loads and routing optimization. The analysis of convergence provided by Zhu and Wang [14] will serve as guidance to solving a similar problem for Kelly-Moore. In addition to the optimization model, parameters will be used to explore "out of the box" thinking to present various alternatives to Kelly-Moore to help them find the solution that works best for them based on their real data from years past.

1 Introduction

The world today depends on readily available supplies to conduct business. Now more than ever should there be a focus on optimizing an organization's ability to deliver supplies in a "just-in-time-just-enough" fashion. Businesses can suffer financial risks if inventory levels remain too high with stagnant product. Alternatively, the "hyper-competitive" nature of business today allows consumers myriad choices in their ability to fulfill their needs. If the organization is not capable of keeping up with demand efficiently, they risk losing customers; for good.

"Transportation costs can be a significant part of a company's overall logistics spending. With increases in the price of fuel, the proportion allocated to transportation can be upward of 50 percent" [1]. Supply chain optimization is often considered to be part of "supply chain engineering" which is mainly focused on mathematical modeling. However, supply chain optimization can also be done using qualitative, management-based approaches. There are several methods and ideas on how to solve the financial conundrum of freight optimization. Optimizing delivery routes, time of day forecasting, on-site delivery times, and equipment utilization are age-old questions in optimizing transportation costs.

Leadership teams need answers to the questions of costs, not only in dollars spent/saved, but also, in carrier relationships, end-user "buy-in", as well as the management of related information. Kelly-Moore Paints is a paint manufacturing company founded in San Carlos, California in 1946 by William Kelly and William Moore. Their main competitors are Sherwin-Williams, PPG and Benjamin Moore. They primarily serve stores located in California, Texas, Oklahoma, and Nevada. They have only one manufacturing plant which is located in the heart of the Dallas/Fort Worth Metroplex, Hurst, Texas. In addition, they have distribution centers in Texas and California. The Texas distribution center services about 44 stores while the California distribution center services about 120 stores.

Their logistics operations are staffed as a privately-owned operation consisting of Kelly-Moore owned 42' trailers and four dedicated contracted tractor operators. Utilizing data regarding the use of these trailers and dedicated line-haul, the goal will be to explore opportunities of efficiencies in load utilization and routing. In business for almost 75 years, Kelly-Moore has obviously adopted best practices rooted in the logistics problem of moving supplies across the US. All great leaders are constantly looking to improve efficiency and never assume that the current way of doing business is the best and only way. The leadership team is advocating thinking "outside of the box" and discover alternative methods that are more automated, accurate, and precise.

Most of the time a team of people are manually observing data and making decisions months or quarters in advance to properly plan the supply chain. The organization would like to be more "agile" in decision making and use empirical data to optimize line-haul operations paired with short-haul response to store needs. The single most important question that leadership has on their mind: "What is the best way to ensure the scarce trailers are utilized effectively?".

The Texas Distribution Center services 44 stores in the Dallas/Fort Worth Metroplex and a few stores sporadically located in Oklahoma as well as other parts of Texas. The stores currently are supplied with a "milk-run" type auto-replenishment of inventory twice per week with same day delivery. The store managers are presented with tools that recommend projected inventory to order from the Texas Distribution Center. They then place their orders twice a week. The key to optimizing the routes revolve around the store ordering patterns as well as the demand routing to ensure the eleven trailers are optimized for the locations they are servicing.

Could the use of data science techniques allow Kelly-Moore to see trends in their line-haul and make adjustments to optimize one of the costliest parts of the supply chain transportation? Using the domain expertise of Kelly-Moore's operations and SMU's Data Science technology expertise, the hypothesis is that Kelly-Moore can streamline how to harvest their data and learn to clean the data for use in proven methods to predict and model the supply chain line-haul in ways they may not have been aware of in the past.

Kelly-Moore leadership has recognized that many of the trailers that are leaving the distribution centers are not optimized for the DFW routes. Some trailers are leaving with only a few pallets. One 42' trailer can hold up to 20 pallets consisting of roughly 36,000 pounds of product.

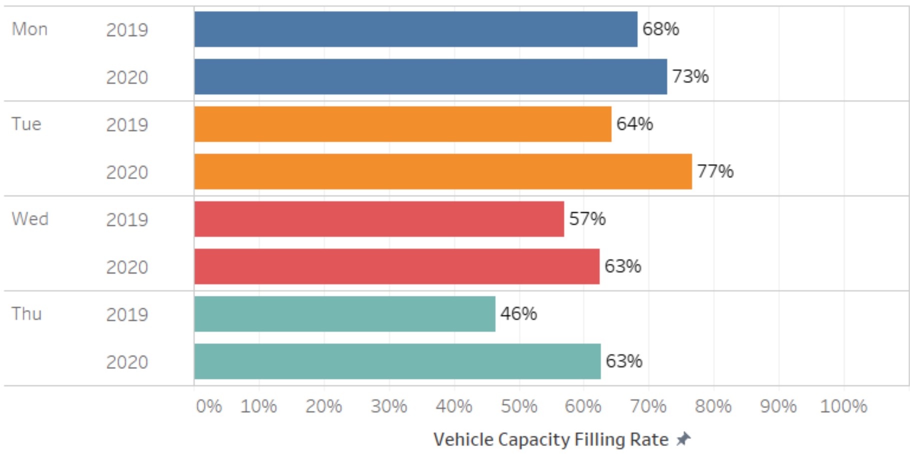


Fig. 1. Trailer filling rate summary. Consistent with the visualization, is the fact that the rates vary significantly by day of the week.

2 Literature Review

Fortunately, supply chain operations are an industry focus with countless goods relying on the distribution network of the US GDP. These movements don't "just happen", they are well intended and planned orchestral exercises in efficiency and planning. Kelly-Moore might be a small operation compared to the US GDP, but the business problems and solutions framework are essentially the same. The goal is to move the product Kelly-Moore creates to its store fronts, which is the only way to buy the paint, and ensure the scare resources that actually move the freight are optimized according to orders, routing, and sorted trailers. FedEx is often thought of as the king of this space. There is much to learn from evaluating how FedEx takes a seemingly infinite number of packages and spreads them over scarcely available aircraft and trailers to meet the demands of their customers; overnight.

December is often the largest season at FedEx, which is called Peak Season to its employees. As people are going about their lives planning for Christmas and having parties, FedEx employees are the busiest they will be all year. Kelly-Moore has eleven trailers to work on optimization. FedEx has over 600 planes and 70,000 trucks [13]. Surely, FedEx can be studied, and a few pages taken from their playbook. While Kelly-Moore won't likely require twelve meteorologists watching forecasts or standing up a Global Operations Control Center (GOCC) [13] to manage the chaos each and every day like FedEx, they do need a good system of planning for their stores relative to their operation.

The goal of this paper is to explore the best routing for the network; utilizing real data in order to predict orders and optimize routes with available trailers. This paper will also explore how Kelly-Moore can reduce deliveries to one day per week while instituting some of FedEx's best practices as it relates to responding to "problems" in the system. For instance, FedEx flies two empty airplanes every night from its Denver and Salt Lake City Ramps [13]. Is it possible that Kelly-Moore can reduce standard deliveries to one time a week and provide empty trailers along various routes to do ad-hoc type runs? Would that be cheaper than sending all routes two times a week? These are all questions that can be answered by data and the algorithms employed to predict and fine-tune the routing mechanisms.

Given that this logistics problem is fundamentally about probability, the employment of probabilistic algorithms can be explored by searching the solution space more efficiently using probability to prioritize search areas; narrowing down where the optimal solution might reside. An approach to consider revolves around a well-known traveling salesman problem. The routing can be optimized based on the one-to-many relationship akin to multiple salesmen (i.e. trailers) [8]. The computational problem is NP-hard and scales poorly due to the solution space becoming too large. This leads to another approach to consider; the Ant Colony Optimization (ACO) algorithm. The algorithm has been studied for the traveling salesman problem in one-to-many [14] and many-to-many distribution settings [7]. The goal is to tune for a globally optimal solution given the current centralized distribution center setup as well as finding solutions for alternative hub and spoke models by adjusting the algorithm. This approach allows for convergence to the optimal solution which can be achieved from an initial set of parameters, minimizing search parameter spaces akin to fitting a machine learning algorithm.

3 Methods

The stores in the Southwest Region are provided two shipments per week. The shipments are generated by an auto-replenishment order from a robust planning tool. Whenever a store needs more than the recommended order, additional product could be added to the order or a separate order will be placed at a later time. The additional orders could come in by a regular store order or a will-call order. Will-call orders are picked up at the warehouse by the stores usually with-in a 24-hour window. The standard deliveries run Monday thru Thursday with many of the trailer routes less than 50% capacity throughout the week. Simply focusing on optimizing the routes that are less than 50% capacity could significantly reduce the overall transportation costs. This paper will center on the following two objectives:

- Forecast weekly sales data for individual store (predict)
- Matching the trailer availability data, provide the best set of paths between the stores that optimizes load factor and reduces freight costs

3.1 Data

The stores currently receive order recommendations from an automated system using inputs from the point-of-sales system. The data interface includes daily store inventory, historical sales and future sales. The current culture of the organization implies that the stores largely ignore the recommendations and order their shipments with little regard for the larger transportation costs. The plan will focus on modeling the data elements to predict the store's needs and reduce deliveries to one time a week. There will be an option to fulfill orders that are required for low inventories on an ad-hoc basis. The algorithm will be turned to pre-determine orders for a store, make a recommendation, and ensure the stores receive shipments with optimized trailers.

Exploring the data available from the domain experts allows for experimentation with various ideas and ultimately decide if more data is needed or if alternative timelines are warranted. Kelly-Moore sales are cyclical with sales volume increasing in warm summer months and decreasing during damp cold months. Considering the cycle of sales, all of the data captured is for the given time period of Year-to-Date 2019 through July 2020 ("given time frame" or "time period"). There are 44 stores in the Southwest region that make up Oklahoma, West Texas, North Texas or Dallas-Fort Worth ("DFW") and South Texas. The stores are scheduled to receive two orders each week, either Monday and Wednesday or Tuesday and Thursday.

The data provided comes from four data sources; current delivery manifest, which includes freight metrics, order detail from the ERP, recommended orders from the planning tool and sales from the POS. Some of the key metrics tracked on the manifest are load weight, miles and location. The order detail includes PO numbers, unique store numbers, SKU information such as item description and quantity ordered. There are roughly 164 potential order days for store regular orders (using their scheduled order days). Of note in the first round of analyzing this data are the following:

- Store Add-On Orders are additional store orders that have to be approved by a warehouse manager. These orders are generally held until the store's regular order day. There are six stores outside of the DFW area that placed add-on orders in the given time period. Of the 44 stores there are eleven stores in the DFW area that placed add-on orders.

- A Store Quick-Turn and a Will-Call order are for unique circumstances. A quick turn is an order for a special product that store orders from the Kelly-Moore Manufacturing plant. Five stores placed a quick turn order and only one of those is a DFW store. Will-Call Orders occur when a store places an order on the warehouse and will pick up from the warehouse within 24 hours. The warehouse is in Hurst, Texas which is in the DFW metroplex. Wichita Falls is the only store not in DFW that placed a will-call order. Not including the Hurst Retail store, sixteen of the nineteen North Texas stores placed will-call orders. The eight stores that ordered less than 90% of their scheduled order days have an average will-call order of 26 orders. This is an indication that the store is not utilizing their schedule orders effectively and ultimately impacting trailer optimization.
- Store Regular Orders are orders placed on the store's scheduled order day. Stores can place more than one order on their scheduled order day, and it is considered a regular order and not an add-on. There are approximately 164 possible order days in the given time period. All of the stores outside of the North Texas market are ordering at 90% or better of their ordering days with the exception of Temple, which is a new store. Of the nineteen North Texas stores, there are eight that are below 90% utilization of order days. Three of the eight are new stores.

3.2 Forecasting Problem

Predicting the weekly sales of individual stores allows Kelly-Moore to have some idea of its upcoming logistical needs. Individual weekly store sales have a spatial, temporal, and idiosyncratic component to them. While this complicates the modeling process, these components can be leveraged to improve the accuracy of the predictions. It is anticipated that a hierarchical multilevel method with Dirichlet process or Gaussian process priors will ultimately prove to be the resulting model that will be used.

Hierarchical methods ultimately require an assumption that the observation in the data are exchangeable, which means that switching ordered indices in the data (i.e., time, space, etc.) will not matter when it comes to the aggregate behavior of the data [15]. Exchangeability is obviously problematic in time series data, spatial data, and situations where differences between products are important because those observations almost always have relevant heterogeneity. The forecasting solution will depend on explicitly modeling the relevant temporal, spatial, and idiosyncratic components that drive sales across stores.

Information from domain experts at Kelly-Moore suggests that there is a strong non-stationary component to weekly store sales across time; however, it is best to check to ensure the data is consistent with this domain expertise. In addition, this will allow for future checks when the model is deployed.

Figure 3: Temporal Characteristics of the Data

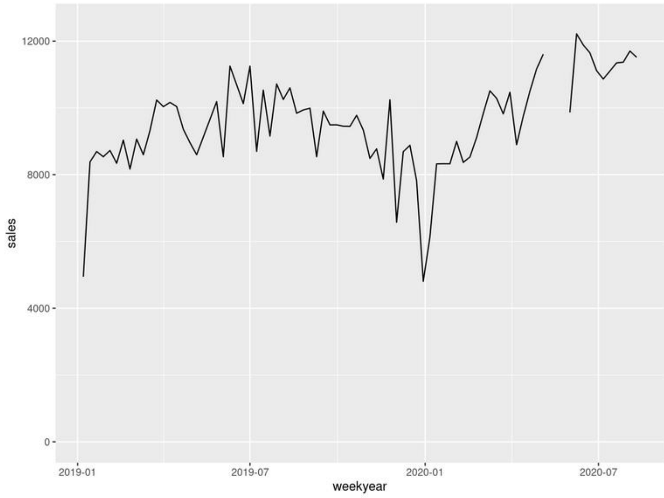


Fig. 3. Temporal Characteristics of the Data. There is a clear impact of COVID-19 in the beginning of 2020, but actual moving of sales tends to be on the rise even greater than 2019.

The temporal nature of the data will need to be a factored into this analysis given that timing is critical to the nature of the business operations. Optimization criteria are traditionally time, distance, and cost. In modern times, tremendous data is available and can be gathered from smart cards and GPS tracking as well as speed of travel, start/stop attributes, and load utilization. Geographical coordinates along the delivery routes will be pivotal in understanding the optimized routing. Paired with the order information from the stores (as well as inventory on hand), the algorithm can further explore recommended inventory requests as well as fine-tuning the frequency of delivers in the Monday-Thursday delivery days. It will be necessary to distill this data in order to gain the advantages of various data analysis techniques.

The first step was simply to visualize the temporal nature of the data.

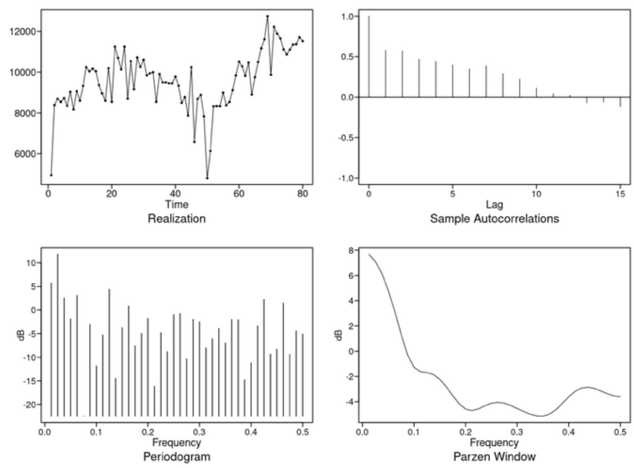


Fig. 4. Detailed Temporal Characteristics of the Data. Detailed comparisons with frequency and Parzen Windows analysis. Strongly suggests non-stationary temporal behavior.

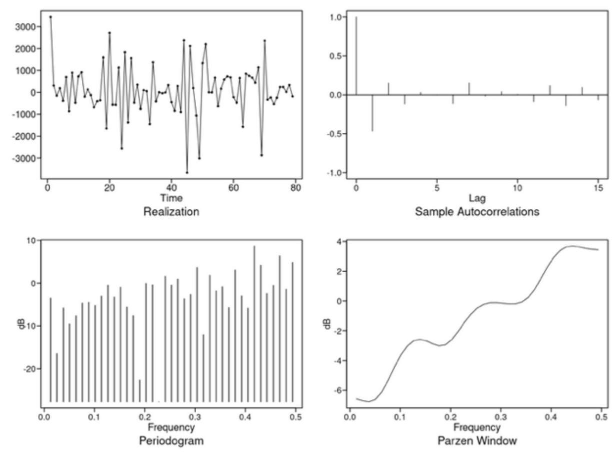


Fig. 5. Detailed Temporal Characteristics (filtered with a first difference). There currently doesn't appear to be any dominating periodicity within the past year, which is consistent with the domain expertise at Kelly-Moore.

To provide a more detailed analysis of the temporal characteristics of sales, analyzing more data in previous years is warranted.

3.3 Optimization Problem

The solution chosen to optimize Kelly Moore's trailer space utilization is based on the observation that finding the number of trailers for which the total cost of distribution is minimized will necessarily optimize trailer space utilization. Keeping the shipment quantity fixed, fewer trailers will mean that each individual trailer will use extra space and this project defines the optimal space utilization to be the one that minimizes the total cost of distribution. This conveniently allows for the complicated problem at hand to be recast as a simpler Multiple Traveling Salesman Problem.

The trailer space optimization problem for Kelly Moore is an instance of a Multiple Traveling Salesman Problem (MTSP). The MTSP is an NP-hard computational problem, meaning that there is almost certainly no efficient way to solve the problem in an efficient and deterministic manner [16]. The central complication is that multiple different trailers each with multiple different possible routes creates a massive space of possible solutions. Fortunately, there are probabilistic solutions to the MTSP that are much faster and are likely to converge to the global optimal solution in a relatively short amount of time, such as Ant-Colony Optimization algorithms [17]. This project uses an Ant-Colony Optimization (ACO) approach to solve the problem of trailer space optimization for Kelly Moore Paints.

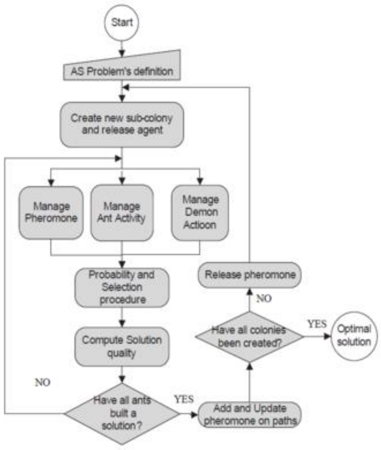
ACO is a meta-heuristic algorithm that was inspired by the foraging behavior of ants. Ants initialize the foraging process at their colony and begin searching in random directions for any food source they can find. The moment an ant finds food, they take a piece of that food and return it to their colony while leaving behind a pheromone trail on the ground. The other ants are attracted to this scent and begin following it back to the food source and leave pheromone trails themselves. In general, ants will follow whichever pheromone trail has the strongest scent and because pheromone trails evaporate, the strongest pheromone trail will eventually be the shortest path to the food source [18]. The ACO algorithm described in this paper will use *artificial ants* instead of real ants to find the optimal routes for a given number of trailers. The algorithm will be run several times with different quantities of available trailers at each iteration to find which number of trailers minimizes the total cost of distribution.

This paper will utilize an ACO algorithm based on Liu et al [17]. They represent an MTSP as a weighted, non-directed graph G (V, E), where V denotes the vertices of the graph and E denotes the edges between the nodes. Each vertex v_j represents a destination and the route between each destination is represented by an edge, which they denote as e_i. A weight function $w(e_i)$ represents the cost of transporting freight between city v_i and v_j. Because every trailer must return to the origin, each route should end up as N closed loops beginning and ending at the origin hub: $L_1, L_2, \ldots, L_N$. We denote $w(L_i)$ as the cost of the closed loop L_i. The optimization problem can then be characterized as follows:

- Objective Function
- Constraints
- Decision Variables
- Pheromone Update Function

```
Input: Instance x ϵ I of Π_opt
        Set algorithm parameters ()
        i, j ← 0
        for j= 1 to colonies do
            Ant s_0 ← Create sub-colony and release
             agent
             while not-termination conditions
                   on sub-colony do
                     i=i+1
                     Manage_ants activity ()
                     Manage_Pheromone ()
                     Manage_Demon Action ()
                     Selection Procedure ()
                     Compute solution Quality ()
             end while
             j=j+1
             S_best←candidate to be optimal solution
             Update pheromone on arc ()
         end for
Output: S_best"candidate" to be the best found
                   solution x ϵ I
```

(a)



(b)

Fig. 6. The Ant Colony Optimization (ACO) model; a. the pseudo-code of an ACO algorithm; b. the flow chart of a general ACO procedure. [19]

4 Results

The Ant Colony Optimization (ACO) has been applied in many fields and after exploring the pieces of data offered here at Kelly-Moore Paints, it could be a valid approach to model freight optimization and order prediction. After careful research of how this approach has been experimented with in similar data sets, it could lead to valid convergence conclusion.

In principle, the model ought to be able to not only find global optimal solutions for the current setup, but it will also be able to find optimal solutions for alternative setups (alternatives to the current hub and spoke model) by making small adjustments to the algorithm. The thinking is that the algorithm can simultaneously answer optimal sorting between and within the trucks, optimal paths, and whether Kelly-Moore can adjust the structure of the supply chain itself by adding more distribution centers or making more areas "hubs" and then compare those configurations to the current setup.

An area of concern is the assumption that Kelly-Moore wants their trailers as full as possible, but this algorithm that is being explored, relaxes that assumption. Alternatively, if full trailers are better, it will arrive at that conclusion naturally. The current results contain some claimed proofs of convergence for a specific ant colony algorithm [7]. More time was spent thinking through whether the assumptions generalize to the Kelly-Moore use-case. Given the problem at hand is a probabilistic algorithm, convergence will be a key element to watch. This is also the case for a traveling salesman problem, which is one-to-many instead many-to-many. The current Kelly-Moore setup implies a traveling salesman problem; therefore, this kind of result is still required in order to show what happens under a hub and spoke model. If this project can be centered on applying the ant colony optimization [14] to Kelly-Moore's supply chain, both a firm problem statement and almost everything leadership wants can be achieved.

A positive outcome about this algorithm is that convergence to the optimal solution can be achieved from any initial set of parameters, unlike fitting an ML algorithm. Sometimes convergence can be achieved even when the assumptions are not met, and instances of that alone are incredibly valuable to practitioners.

For example, the team compared five solution instances based on typical order data by applying different iteration thresholds while keeping the number of vehicles, the pheromone and the heuristic parameter the same. Figure 7 demonstrates the solution presented with less iteration threshold; a good distance reduction result compared to a more iterations case. In a case where time to converge matters more and a good enough solution is acceptable, the ACO can be a good tool for supply chain practitioners.

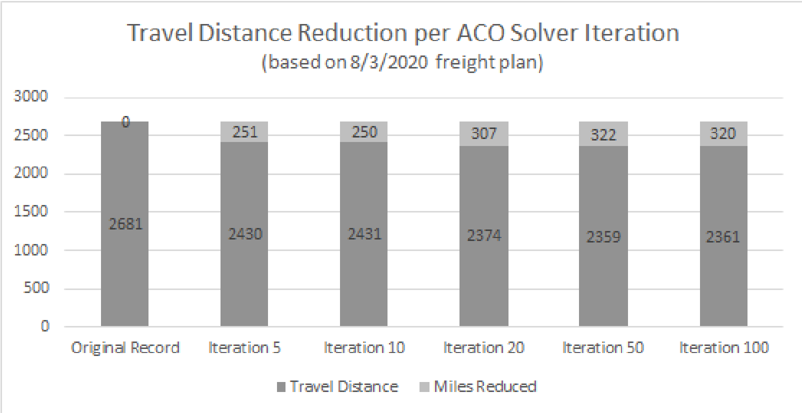


Fig. 7. The Outcome of The Converged Solutions from Different Parameter Sets

The routes are plotted visually to determine if the solution suggested by ACO is acceptable in terms of similarity to the historical route records. Each visit plan is centered around store clusters and the round trip to remote area is familiar to previous travel known to vehicle drivers.

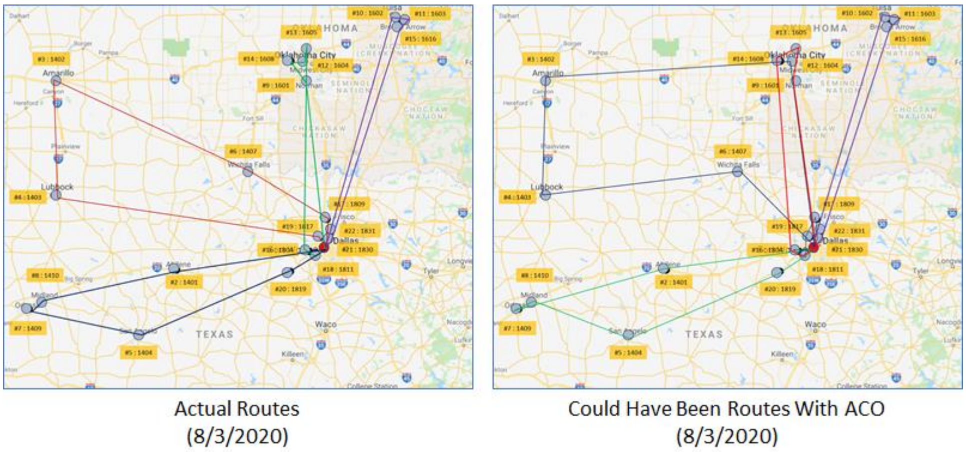


Fig. 8. The Scheduling Route Comparison

5 Discussion

Of great business consequence found, is the convergence to the solution that can be achieved from any set of initial parameters. This is helpful for various business situations, changing processes, and rules. For instance, a solution can be found for a fixed number of vehicles, as well as the algorithm's ability to bring the optimized routes using a minimum number of vehicles. Setting the iteration threshold to a certain number is also helpful when the business users need to make revised route decisions in a short period of time.

To apply this scenario, Kelly-Moore should consider implementing the ACO route optimization model to the Southwest stores. The model can be modified at the site level to generate the optimal route based on store order days and can potentially determine if two orders a week are even necessary. Kelly-Moore will be maximizing driver efficiencies, delivery times, and reducing fuel usage and maintenance which contribute to an annual cost savings.

The team adopted the MSTP ACO library developed by Yu Iwasaki [22]. Python Network X libraries are used to convert the proprietary PO (Purchase Order) data into a Graph format consisting of nodes and edges. In addition, the API was containerized so that the service can run on the business machines of warehouse managers with minimal complexity exposed to end users. For example, it took 2 minutes, with a typical business laptop computer, to get the scheduling routes for 22 stores utilizing four vehicles: the typical requirement for an average day. This is promising since the scheduling does not require much computing power or infrastructure. It is anticipated that containerization contribute to the future integration with the internal business application of the organization.

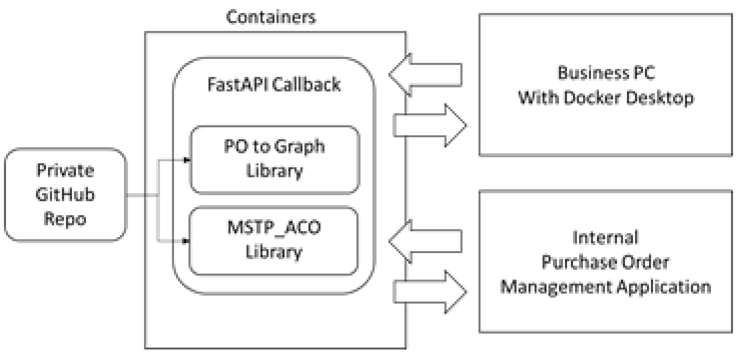


Fig. 9. Containerization of ACO Library to Service Optimization as API

For future expansion, a process can be added to find the optimal alpha (pheromone) and beta (heuristic coefficient) as a part of the solver function. The distance saving from Fig.7 is based on the fixed set of alpha (1) and beta (3) value that is found from a grid search to past data. Applying heterogeneous values per each ant [21] can be a good alternative that can be explored at a later time.

Ethics should be considered anytime data from a person or organization is being utilized. Naturally the data provided by Kelly-Moore should remain confidential to the organization. The collection and storing of data remained in a private cloud which was inaccessible to unauthorized agents. The production version of the algorithm and container will remain behind corporate firewall protection ensuring only authorized agents may consume the data and optimization factors.

6 Conclusion

Ant Colony Optimization performed well enough to solve the multiple travelling salesmen problem that has np-hard complexity. As discussed, the algorithm uses artificial ants to find the optimal routes for a given number of trailers with probabilistic variables that mimic decaying pheromone of the ants or in this case, trailers.

There are efficiencies that can be gained with further exploration in the field with Kelly-Moore Paints. The algorithm is solid enough to find enough optimized routes while raising the trailer capacity utilization as explored in the cost-savings section. The speed and minimal computing power consumption provided by Julia and Docker containerization surface another benefit as the project adopted ACO. The deployed solution could run on a simple business machine that the logistics team could then adjust for the week's orders at a time, allowing the team to be more agile in their decision making. As the team uses the tools to assist in planning the supply chain routing, the algorithm can be refined further for Kelly-Moore's specific needs. This project proved another exciting application in the world of data science techniques and technology.

When time permits, the team would explore how this optimization could be utilized for various supply chain operations outside of Kelly-Moore. An exciting exploration at the time of this project would be to coordinate the distribution of COVID-19 vaccines utilizing this particular algorithm. An interesting tactic that was discovered was to route patients to the closest hospital using the same type of ACO optimization [23]. For the focus of this project, it is believed that very few modifications would need to be made to apply the same logic given the data available for hospital routing or even vaccine distribution data. Perhaps in the future the team can provide further experiments and report the application of such an endeavor.

Acknowledgments. David Stroud (advisor from SMU) and Bruce McGregor VP of Supply Chain at Kelly-Moore Paints.

References

1. Murphy, M. (2019, July 29). Reducing Supply Chain Transportation Logistics Costs. Moving Products Efficiently. https://www.thebalancesmb.com/reducing-transportation-costs-2221049
2. Latunde, Tolulope & Richard, Joseph & Esan, Opeyemi & Dare, Damilola. (2020). OPTIMAL FEASIBLE SOLUTIONS TO A ROAD FREIGHT TRANSPORTATION PROBLEM. MALAYSIAN JOURNAL OF COMPUTING. 5. 456-468. 10.24191/mjoc.v5i1.7786.
3. Sert, Egemen & Hedayatifar, Leila & Rigg, Rachel & Akhavan Masoumi, Amir & Buchel, Olga & Saadi, Dominic & Kar, Aabir & Morales, Alfredo & Bar-Yam, Yaneer. (2020). Freight Time and Cost Optimization in Complex Logistics Networks. Complexity. 2020. 1-11. 10.1155/2020/2189275.
4. Lamiraux, Florent & Laumond, Jean-Paul & Geem, Carl & Boutonnet, Daniel & Raust, Gilbert. (2005). Trailer-truck trajectory optimization - The transportation of components for the Airbus A380. Robotics & Automation Magazine, IEEE. 12. 14 - 21. 10.1109/MRA.2005.1411414.
5. Nguyen, Truong & Zhou, Li & Spiegler, Virginia & Ieromonachou, Petros & Lin, Yong. (2017). Big data analytics in supply chain management: A state-of-the-art literature review. Computers & Operations Research. 10.1016/j.cor.2017.07.004.
6. Dong, C., & Zhou, L. (2018). Optimization Algorithm for Freight Car Transportation Scheduling Optimization Based on Process Scheduling Optimization. 11067, 528–538. https://doi.org/10.1007/978-3-030-00018-9_46
7. Barcos, L., Rodríguez, V., Álvarez, M., & Robusté, F. (2010). Routing design for less-than-truckload motor carriers using Ant Colony Optimization. Transportation Research. Part E, Logistics and Transportation Review, 46(3), 367–383. https://doi.org/10.1016/j.tre.2009.11.006
8. Prokudin, G., Chupaylenko, O., Dudnik, O., Dudnik, A., & Pylypenko, Y. (2018). Traveling salesman problem in the function of freight transport optimization. Journal of Sustainable Development of Transport and Logistics, 3(1), 29–36. https://doi.org/10.14254/jsdtl.2018.3-1.3
9. Ghalehkhondabi, Iman, Ahmadi, Ehsan, & Maihami, Reza. (2020). An overview of big data analytics application in supply chain management published in 2010-2019. Production, 30, e20190140. Epub June 01, 2020. https://doi.org/10.1590/0103-6513.20190140
10. Sumit Maheshwari, Prerna Gautam & Chandra K. Jaggi (2020) Role of Big Data Analytics in supply chain management: current trends and future perspectives, International Journal of Production Research, DOI: 10.1080/00207543.2020.1793011
11. Wang Y., Liu Y., Zhang C., Li Z. (2013) Finding the Optimal Bus-Routes Based on Data Mining Method. In: Huang DS., Bevilacqua V., Figueroa J.C., Premaratne P. (eds) Intelligent Computing Theories. ICIC 2013. Lecture Notes in Computer Science, vol 7995. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-39479-9_5
12. Kasturi, E. & Devi, S. & Kiran, S. & Manivannan, S.. (2016). Airline Route Profitability Analysis and Optimization Using BIG DATA Analyticson Aviation Data Sets under Heuristic Techniques. Procedia Computer Science. 87. 86-92. 10.1016/j.procs.2016.05.131.
13. Deutsch, C. (2003). 'Planes, Trucks and 7.5 Million Packages: FedEx's Big Night', The New York Times, New York, 21 December. Available at: https://www.nytimes.com/2003/12/21/business/planes-trucks-and-7.5-million-packages-fedex-s-big-night.html (Accessed: 29 October 2020).
14. Zhu, Q., Wang, L. The analysis of the convergence of ant colony optimization algorithm. Front. Electr. Electron. Eng. China 2, 268–272 (2007). https://doi.org/10.1007/s11460-007-0049-0

15. Gelman, A., Carlin J., Stern H., Dunson D., Vehtari A., Rubin, D. (2020). Bayesian Data Analysis (3rd ed.). CRC Press.
16. Moore, C., Morris, S. (2011). The Nature of Computation. Oxford University Press.
17. Liu W., Li, S., Zhao F., Zheng A. (2009). An Ant Colony Optimization Algorithm for the Multiple Traveling Salesmen Problem. 2009 4th IEEE Conference on Industrial Electronics and Applications, Xian, 2009. 1533-1537. 10.1109/ICIEA.2009.5138451.
18. Nayyar A., Le N., Nguyen N. (Eds.). (2019). Advances in Swarm Intelligence for Optimizing Problems in Computer Science. CRC Press.
19. De Felice, Fabio, Petrillo, Antonella, Monfreda, Stanislao. Improving Operations Performance with World Class Manufacturing Technique: A Case in Automotive Industry. Open Textbooks for Hong Kong (2016). http://www.opentextbooks.org.hk/ditatopic/27149
20. Min Wang, Tongmao Ma, Guiling Li, Xue Zhai, Sibo Qiao. Ant Colony Optimization With an Improved Pheromone Model for Solving MTSP With Capacity and Time Window Constraint (2020)
21. Fayeez, A; Keedwell, E. A Heterogeneous Ant Colony Optimisation approach with Application to the Travelling Salesman Problem (2017)
22. Yu Iwasaki, University of Tsukuba (https://github.com/Ganariya/MTSP_ACO)
23. C. Guevara and M. S. Peñas, "Surveillance Routing of COVID-19 Infection Spread Using an Intelligent Infectious Diseases Algorithm," in IEEE Access, vol. 8, pp. 201925-201936, 2020, doi: 10.1109/ACCESS.2020.3036347.

Appendix:

Fig. 1. Trailer utilization by day of week. Of note is how most of the trailers were not going out full. The redder the square, the less optimized it is for that day of the week. In this visualization we can see the trends clearly to lead us down the next path in the data.